

# Simulation of Flexible Manufacturing System using Adaptive Neuro Fuzzy Hybrid Structure for Efficient Job Sequencing

Rajkiran Bramhane, Arun Arora, H. Chandra

**Abstract**— *The Flexible Manufacturing Systems (FMS) basically belongs to a category of productive systems in which the main characteristic is the simultaneous execution of several processes and sharing a finite set of resource. Analysis and modeling of flexible manufacturing system (FMS) includes priority analysis of machining jobs and machining routing for efficient profit and production. Flexible manufacturing system (FMS) job Priority calculation becomes exceptionally complex when it comes to contain frequent variations in the part designs of incoming jobs. This paper focuses on priority analysis of variety of incoming jobs into the system efficiently and maximizing system utilization and throughput of system where machines are equipped with different tools and tool magazines but multiple machines can be assigned to single operation. For the complete analysis of the proposed work, a cloud of four incoming jobs have been considered. The Jobs have been assigned the priority according to Slack per Remaining Operations. Usually the probability of incoming job priority is calculated based on three parameters based strategy. In this work an adaptive Neuro fuzzy inference system (ANFIS) is developed to calculate the priority of incoming jobs based on Slack per Remaining Operations (S/RO) parameter. Four horizontal CNC lathe machines have been utilized for this work. Therefore, in this paper, an ANFIS system is developed to generate best priority of incoming jobs. The results obtained clearly indicate the higher efficiency of the proposed work to decide the priority of the incoming jobs.*

**Key words:** flexible manufacturing system (FMS), adaptive Neuro fuzzy inference system (ANFIS), Slack per Remaining Operations (S/RO), Incoming job priority.

## I. INTRODUCTION

A flexible manufacturing system (FMS) is a manufacturing system in which there is some quantity of flexibility that allows the system to respond in the case of changes. Flexible manufacturing systems have been developed to combine the flexibility of job shops and the productivity of flow lines. Such systems consists of three sub-systems: a processing system including a number of CNC machines, an automated material-handling system to link these machines, and a computer control system controlling the operation of the whole FMS. It also consists of load and unload stations, inspection stations, along with storage regions and a hierarchical managing control system. In general when it is being planned, the purpose is to design a system which will be proficient in the fabrication of the entire range of parts. This cannot be completed until the entire stages work fine.

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Based on the required level of scheduling performance, many dissimilar approaches can be generated. However, scheduling of an FMS is very problematical, particularly in dynamic environment. Many manufacturing systems, therefore, need scheduling for dynamic and unpredictable conditions. So, simulation based scheduling have been considered in FMS scheduling. Fuzzy logic, which was originally introduced by Zadeh (1965), has been applied to a variety of industrial problems. The advantage of the fuzzy logic approach is that it incorporates both numerical results from previous solutions or simulation and the scheduling expertise from observed data, and it is very easy to implement. Several Fuzzy logic based scheduling systems have recently been developed. Watanabe proposed a fuzzy scheduling mechanism for job shops, that they name FUZZY. The only problem that they actually attack is the priority setting problem for a free machine choosing in its buffer the next job to serve. Grabot gave a routing mechanism that embodies expert knowledge and that reacts to resource failures by using fuzzy logic and possibility theory. Angsana and Passino have proposed a new scheduling method which was designed to imitate human scheduler. The implemented Fuzzy Controller (FC). Sentieiro employed fuzzy set theory in a non-classic approach called FLAS (fuzzy logic applied to scheduling) for short term planning and scheduling. Most of the time it is found that, the scheduling idea is lies around the individual logics like fuzzy, ANN and genetic optimization. This work brought forward a novel idea for scheduling by employing the fusion of two different fields neural network and Fuzzy logic. An adaptive Neuro fuzzy inference system (ANFIS) is developed to calculate the priority of incoming jobs based on Slack per Remaining Operations (S/RO) parameter.

## II. SCHEDULING SERVICE AND MANUFACTURING PROCESSES

The scheduling techniques can cut across the various process types found in services and manufacturing. Many stable services are characterized by a front-office process with high customer contact, different direction work flows &, consequently, a complex scheduling environment. Often customer demands are very much a difficult prediction, which puts a high cost on scheduling employees to handle the varied needs of customers. Inanimate objects are processed; these processes take on the appearance of manufacturing processes.

Manufacturing processes also benefit from operations scheduling techniques. The operations scheduling techniques in this chapter has application for job, batch, and line processes in services as well as in manufacturing. Schedules for continuous processes can be developed with the help of linear programming. Scheduling techniques in this chapter provide some structure to the selection of good schedules; many alternatives typically need to be evaluated. We begin by looking at the performance measures managers use to select good schedules.

**A. Sequencing Jobs**

Operations schedules are short-term plans designed to implement the sales and operations plan. Often, several jobs must be processed at one or more workstations. Basically, variety of tasks can be performed at each workstation. If schedules are not planned carefully, waiting lines may develop. Figure (2.1) depicts the complexity of scheduling a manufacturing process. When a job order is received for a part, the raw materials are collected and the batch is moved to its first operation. The colored arrows show that jobs follow different routes through the manufacturing process, depending on the product being made. At each workstation, the next job to process is a decision because the arrival rate of jobs at a workstation often differs from the processing rate of the jobs at a workstation, thereby creating a waiting line. In addition, new jobs can enter the process at any time, thereby creating a dynamic environment. Such complexity puts pressure on managers to develop scheduling procedures that will handle the workload efficiently. In this section, we focus on scheduling approaches used in two environments: (1) divergent flow processes and (2) line flow processes. A manufacturer's operation with flows in different directions is often called a job shop, which specializes in low- to medium-volume production and utilizes job or batch processes. The front office would be the equivalent for a service provider. Jobs in divergent flow processes are difficult to schedule because of the variability in job routings and the continual introduction of new jobs to be processed. Figure (2.1) depicts a manufacturer's job shop. A manufacturer's operation with line flows is often called a flow shop, which specializes in medium- to high-volume production and utilizes line or continuous flow processes. The back office can be act as a equivalent for a service provider. Tasks are easier to schedule because the jobs have a common flow pattern through the system. Nonetheless, scheduling mistakes can be costly in either situation.

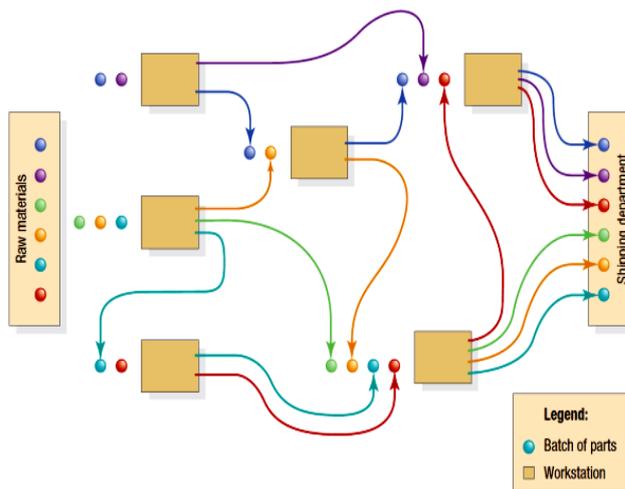


Figure 2.1 Diagram of a Manufacturing Job Shop Process

**B. Job Shop Sequencing**

Just as many schedules are feasible for a specific group of jobs at a particular set of workstations; numerous methods can be used to generate schedules. They range from straightforward manual methods, such as manipulating Gantt charts, to artificial computer models for developing optimal schedules. One way to generate a schedule in job shops is by using priority sequencing rules, which allows the schedule for a workstation to evolve over a period of time. The decision of a job to process next is made with simple priority rules whenever the workstation becomes available for further processing. One advantage of this method is that last-minute information on operating conditions can be incorporated into the schedule as it evolves. The first-come, first-served (FCFS) rule gives the job arriving at the workstation first the highest priority. The earliest due date (EDD) rule gives the job with the earliest due date based on assigned due dates the highest priority. Such rules can be applied by a worker or incorporated into a computerized scheduling system that generates a dispatch list of jobs and priorities for each workstation. Additional priority sequencing rules follow:

- i **Critical Ratio:** The critical ratio (CR) is calculated by dividing the time remaining until a job's due date by the total shop time remaining for the job, which is defined as the setup, processing, move, and expected waiting times of all remaining operations, including the operation being scheduled. The formula is
 
$$CR = \frac{\text{Due Date} - \text{Today's Date}}{\text{Total Shop Time Remaining}} \dots (2.1)$$

The difference between the due date and today's date must be in the same time units as the total shop time remaining. A ratio less than 1.0 implies that the job is behind schedule, and a ratio greater than 1.0 implies that the job is ahead of schedule. The job with the lowest CR is scheduled next.
- ii **Shortest Processing Time:** The job requiring the shortest processing time (SPT) at the workstation is processed next.

iii **Slack Per Remaining Operations:** Slack is the difference between the time remaining until a job's due date and the total shop time remaining, including that of the operation being scheduled. A job's priority is determined by dividing the slack by the number of operations that remain, including the one being scheduled, to arrive at the slack per remaining operations (S/RO).

$$S/RO = \frac{(\text{Due Date} - \text{Today's Date}) - \text{Total Shop Time Remaining}}{\text{Number of Operations Remaining}} \dots (2.2)$$

The job with the lowest S/RO is scheduled next. Ties are broken in a variety of ways if two or more jobs have the same priority. One way is to arbitrarily choose one of the tied jobs for processing next. Although the priority sequencing rules seem simple, the actual task of scheduling hundreds of jobs through hundreds of workstations requires intensive data gathering and manipulation. The scheduler needs information on each job's processing requirements: the job's due date; its routing; the standard setup, processing, and expected waiting times at each operation; whether alternative workstations could be used at each operation; and the inputs from internal or external suppliers at each operation. In addition, the scheduler needs to know the job's current status: its location (waiting in line for a workstation or being processed at a workstation), how much of the operation has been completed, the actual arrival and departure times at each operation or waiting line, and the actual processing and setup times. The scheduler or software uses the priority sequencing rules to determine the processing sequence of jobs at a workstation and the remaining information for estimating job arrival times at the next workstation, as well as determining whether an alternative workstation should be used when the primary one is busy. Because this information may change throughout the day, computers are needed to track the data and to maintain valid priorities.

### III. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

The Sugeno fuzzy inference system works well with linear techniques and guarantees continuity of the output surface (Tan et.al., 2009). We derive the following theorem. Advantages of applying such composite inference methods are that such Sugeno ANFIS model has the ability of learning because of differentiability during computation. The sum-product composition provides the following theorem (Yang et. al., 2000), see in Eq.1 and Eq.2. Final crisp output when using centroid Defuzzification is equal to weighted average of centroids of resulting MFs, where:

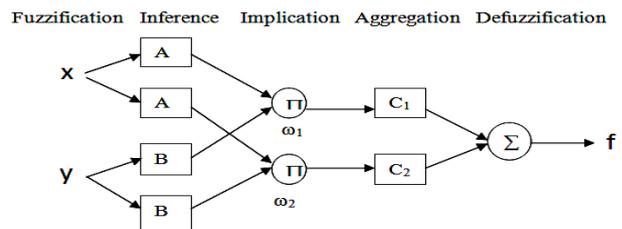
$$\Psi (ri) = \omega (ri) \times a \dots (3.1)$$

where, weighted factor of  $\psi(ri)$  is  $ri$ ;  $ri$  is the  $i$ th fuzzy rule;  $\omega(ri)$  is the firing strength of  $ri$ ;  $a$  is the area of the consequent MFs of  $ri$ .

$$\begin{aligned} Z_{COA} &= \frac{\int_Z \mu_{C'}(z)zdz}{\int_Z \mu_{C'}(z)dz} \\ &= \frac{\omega_1 a_1 z_1 + \omega_2 a_2 z_2}{\omega_1 a_1 + \omega_2 a_2} \dots (3.2) \\ &= \frac{\omega_1 a_1}{\omega_1 a_1 + \omega_2 a_2} \cdot z_1 + \frac{\omega_2 a_2}{\omega_1 a_1 + \omega_2 a_2} \cdot z_2 \end{aligned}$$

Where,  $a_i$  and  $z_i$  are the area and the center of the consequent MF  $\mu_{C_i}(z)$  respectively. According to Eq.3.1 and Eq.3.2, we obtain corresponding Sugeno ANFIS model after some modifications. The overall output  $f$  is given.  $\{b_i, c_i, d_i\}$  are premise parameters and  $a_i, z_i$  are consequent parameters which need to adjust. The type of membership functions (MFs) of the inputs are generalized bell functions, each MF has 3 nonlinear parameters; each consequent MF has 2 nonlinear parameters which are area and center of the consequent part. Totally, there are 16 parameters in this example. A general S-ANFIS model can be expressed as Figure (3.1).

Rule 1: If  $x$  is  $A_1$  and  $y$  is  $B_1$ , then  $Z = C_1$ ;  
Rule 2: If  $x$  is  $A_2$  and  $y$  is  $B_2$ , then  $Z = C_2$ .



**Figure 3.1 General Model of Sugeno ANFIS**

General Sugeno ANFIS architecture consists of five layers; output of each layer is the following.

**Layer 1:** Fuzzification layer.

$$O_{1,i} = \mu_{A_i}(x), i = 1,2; \dots (3.3)$$

$$O_{1,i} = \mu_{B_{i-2}}(y), i = 3,4. \dots (3.4)$$

The membership function is the common bell function.

$$\mu_{A_i}(x) = \frac{1}{1 + \left[ \frac{(x - c_i)}{d_i} \right]^{2b_i}} \dots (3.5)$$

Where  $\{b_i, c_i, d_i\}$  is the parameter set referred to as premise parameters.

**Layer 2:** Inference layer or rule layer

$$O_{2,i} = \omega_i = \mu_{A_i}(x) \times \mu_{B_i}(y), i = 1,2. \dots (3.6)$$

Firing strength  $\omega_i$  is generated with the help of product method.

**Layer 3:** Implication layer

$$O_{3,i} = \omega_i \circ C_i, i = 1,2. \dots (3.7)$$

Implication operator is product.

**Layer 4:** Aggregation layer

$$O_4 = \sum \omega_i \circ C_i, i = 1,2. \dots (3.8)$$

Aggregate operator is sum. The consequent parameters are determined by  $C_i$ . If the consequent MF is trapezoidal membership function, each MF has 4 nonlinear parameters to be adjusted.

**Layer 5:** Defuzzification layer

$$O_5 = D \circ O_4 \dots (3.9)$$

The crisp output  $f$  is achieved with the Defuzzification method, COA (center of area).  $\{b_i, c_i, d_i\}$  are premise parameters. The type of membership functions (MF) of the inputs are generalized bell functions, each MF has 3 nonlinear parameters. If the consequent MF is trapezoidal membership function, then each MF has 4 nonlinear parameters to be adjusted.

Total nonlinear parameters in this example are 20. When there is adequate training data, we can achieve MANFIS model. We can also test the M model by checking data.

**A. Weight Updating Formula**

Weight updating formulas are very important for adjusting S-ANFIS model parameters. In this section, we conclude the weight updating formula for S-ANFIS model by discussing the general weight updating formula based on basic idea of back propagation in NN. An adaptive network is a network structure whose overall input-output behavior is determined by a collection of modifiable parameters (Yang et. al., 2000). A feed forward adaptive network is a static mapping between its inputs and output spaces. Our goal is to construct a network for achieving a desired nonlinear mapping. This nonlinear mapping is regulated by a data set consisting of desired input-output pairs of a target system to be modeled: this data set is called training data set. The procedures that adjust the parameters to improve the network’s performance are called the learning rules. A learning rule explains how these parameters (or weights) should be updated to minimize a predefined error measure. The error measure computes the discrepancy between the network’s actual output and a desired output (Yuanyuan et. al., 2009). The steepest descent method is used as a basic learning rule. It is also called back-propagation (Cheng et al., 1993). Our task is to minimize an overall error measure defined as:

$$E_p = \sum_{k=1}^{N(L)} (d_k - x_{l,k})^2 \quad \dots (3.10)$$

Where, dk is the kth component of the pth desired output vector and xl, k is the kth component of the output vector predicted produced by presenting the pth input vector to the network.

The general weight-updating formula is

$$\Delta\omega_{ji} = -\eta(d_i - x_i) \cdot x_j \cdot X \quad \dots (3.11)$$

Where, η is the learning step, di is the desired output for node i, xi is the real output for node i, xj is the input for node i, X is a Polynomial, usually (xi × (1 - xi)).

**IV. METHODOLOGY**

Analysis and modeling of flexible manufacturing system (FMS) consists of priority analysis of machining jobs and machining routing for efficient profit and production. Flexible manufacturing system (FMS) job probability calculation and routing problems become extremely complex when it comes to accommodate frequent variations in the part designs of incoming jobs. This work has focused on priority analysis of variety of incoming jobs into the system efficiently and maximizing system utilization. For the complete analysis of the proposed work, a cloud of four incoming jobs have been considered. The Jobs have been assigned the priority according to Slack per Remaining Operations. Usually the probability of incoming job priority is calculated based on three parameters based strategy. In this work an adaptive Neuro fuzzy inference system (ANFIS) is developed to calculate the priority of incoming jobs based on Slack per Remaining Operations (S/RO) parameter.

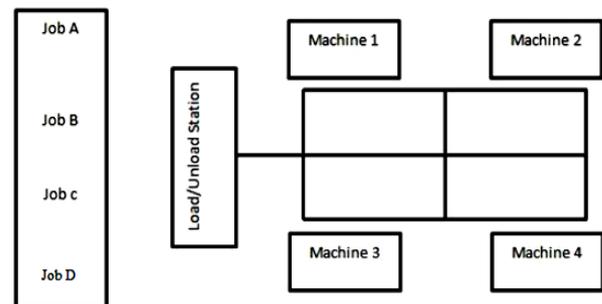
The following assumptions on the FMS were made:

- 1) Each machine can perform a single operation at a time.

- 2) When an operation is started it cannot be stopped until it is completed.
- 3) Each processing step has a processing time with a specific machine.
- 4) Processing time of each job in machine is known in advance.
- 5) All operations of a job are completed according to sequence, before selecting next job.
- 6) Machine grouping, tool sharing & tool duplication is not allowed.
- 7) The machines used are technologically same, and there is only machine of each kind.
- 8) Loading and unloading of jobs, processing times are random.
- 9) Unique routing for job is considered.

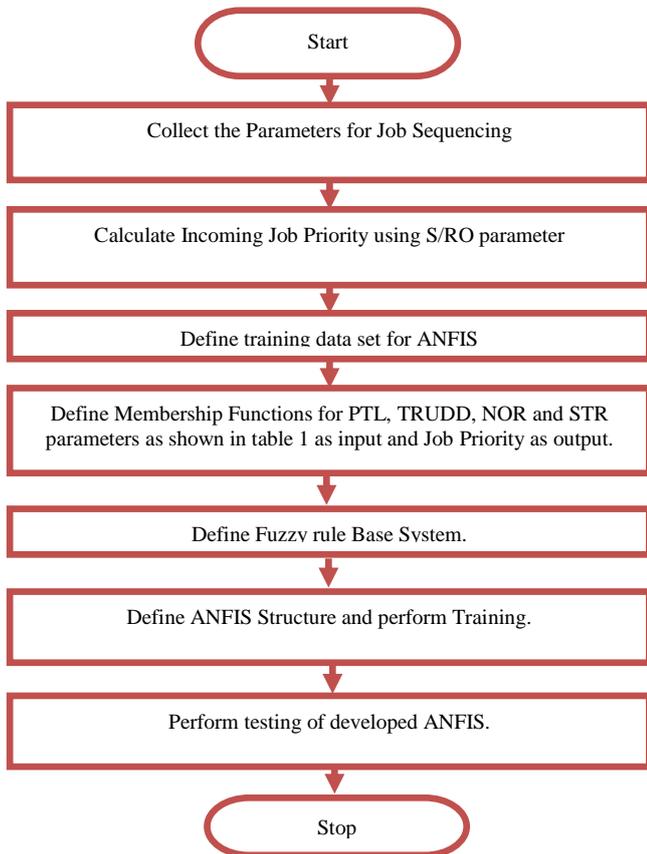
**A. Problem Definition**

The FMS described in this work consists of 4 different CNC horizontal lathe machines, an independent and a self-sufficient tool magazine, one automatic tool changer (ATC) and one automatic pallet changer (APC).The system produces four different parts A, B, C and D. There is a loading station from which parts are released in batches for manufacturing in the FMS. There is an also an unloading station where the finished parts are collected and then they are conveyed to the finished storage. There is also an automatic storage and retrieval system in order to store the work in progress. The arrangement of the FMC hardware is shown in Figure (4.1).



**Figure 4.1 Machining Setup**

Each part has to go through various different routes for completing its different operations. Generally scheduling problem can be stated as to find the best sequence for jobs and then its alternative route is decided. After finding best sequence and route jobs are processed to different machines for performing their respective operations. The complete process of this work is shown in Figure (4.2) with the help of flow chart representation.



**Figure 4.2 Complete methodology of proposed work.**

**B. Development of Sugeno Type Adaptive Neuro Fuzzy Inference System for Incoming Job Priority Calculation**

This section basically deals with the development and simulation of Sugeno Type Adaptive Neuro Fuzzy Inference System for incoming job priority Calculation based on Slack per Remaining Operations (S/RO) parameter. The basic steps taken in the development of above system are:

- Step 1.** Collection of parametric information for all incoming jobs.
- Step 2.** Development and training of Sugeno type Adaptive Neuro fuzzy inference system.

**C. Collection of parametric information for all incoming jobs**

This the first stage for the proposed ANFIS system development. This step basically deals with the all the data collection about all incoming jobs. Like table 7.1 gives the collected data for four different jobs considered for this research work.

**Table 1. Collected Data for Four Different Jobs Considered for this Work**

Job	Processing Time at Lathe (PTL)	Time remaining Until Due Date (Days) (TRUDD)	Number of Operations Remaining (NOR)	Shop Time Remaining (Days) (STR)	S/RO
A	15	12	4	10	0.5
B	10	15	5	7	1.6
C	20.4	12	7	5.5	0.928
D	18	17	8	15	0.25

In table 1 the first four columns represents the required data for all four incoming jobs A, B, C and D. last column represents the output parameter Slack per Remaining

Operations (S/RO) for job priority calculation and hence in this work S/RO is used for job priority calculation.

**D. Development and training of Sugeno type Adaptive Neuro fuzzy inference system.**

Next step is the development and training of Sugeno type Adaptive Neuro fuzzy inference system (SANFIS) for the generation of exact mimic of table 8.1. For the efficient generation of SANFIS model 4 experimental parameter values obtained has been used as shown in table 8.1. Four parameters processing time at lathe, Time remaining until Due date in Days, Number of Operations Remaining and Shop time remaining in Days has been used as four inputs of SANFIS whereas S/RO is taken as the single output. Therefore the developed SANFIS is the four input and single output structure. The other parameters used for SANFIS structure development are given as follows,

```

name: 'MY_ANFIS_SRO'
type: 'sugeno'
andMethod: 'prod'
orMethod: 'probor'
defuzzMethod: 'wtaver'
impMethod: 'prod'
aggMethod: 'sum'
input: [1x4 struct]
output: [1x1 struct]
rule: [1x81 struct]
    
```

After the successful training of SANFIS the average testing error obtained is 1.295x10-8. Figure (4.3) shows the developed FSANFIS ('MY\_ANFIS\_SRO.FIS) basic layout. The rule base designed to get desired S/RO values from SANFIS are given as:

1. If (PTL is in1mf1) and (TRUDD is in2mf1) and (NOR is in3mf1) and (STR is in4mf1) then (JOBPRIORITY is out1mf1) (1)
2. If (PTL is in1mf1) and (TRUDD is in2mf1) and (NOR is in3mf1) and (STR is in4mf2) then (JOBPRIORITY is out1mf2) (1)
3. If (PTL is in1mf1) and (TRUDD is in2mf1) and (NOR is in3mf1) and (STR is in4mf3) then (JOBPRIORITY is out1mf3) (1)
4. If (PTL is in1mf1) and (TRUDD is in2mf1) and (NOR is in3mf2) and (STR is in4mf1) then (JOBPRIORITY is out1mf4) (1)
5. If (PTL is in1mf1) and (TRUDD is in2mf1) and (NOR is in3mf2) and (STR is in4mf2) then (JOBPRIORITY is out1mf5) (1)

.....  
 .....  
 and so on.

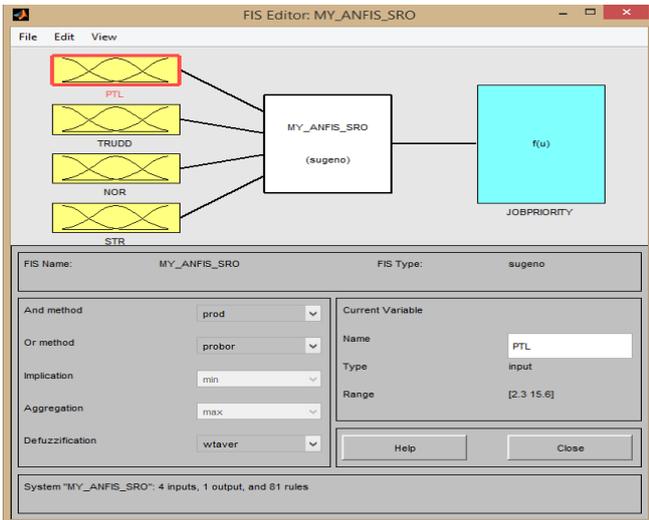
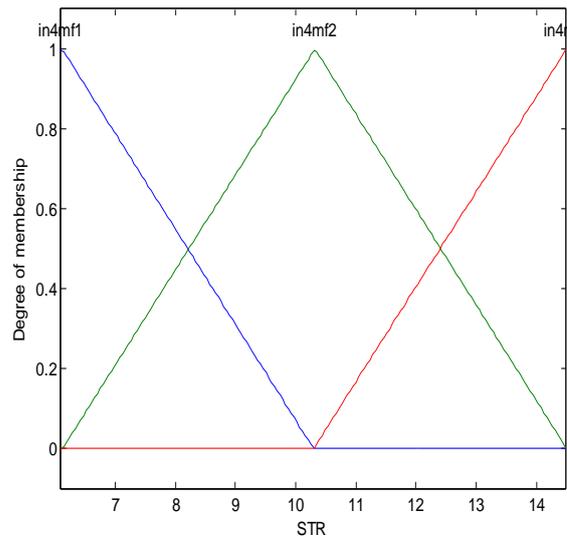


Figure 4.3 developed SANFIS (MY\_ANFIS\_SRO.FIS) Layout

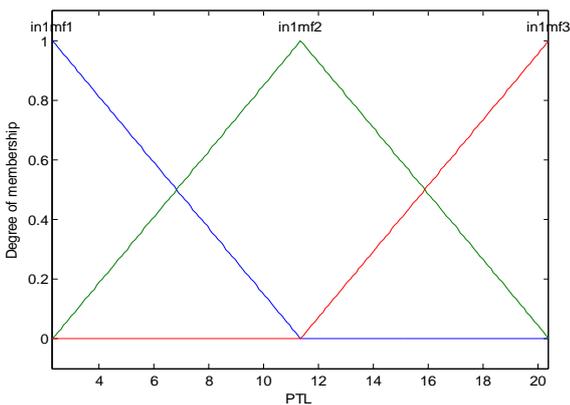
Now figure (4.4) shows the input membership functions for developed FSANFIS, and figure (4.5) shows the basic structure of SANFIS. The output of developed SANFIS is a linear function.

(C) Third Input Membership Functions Used to Fuzzify NOR

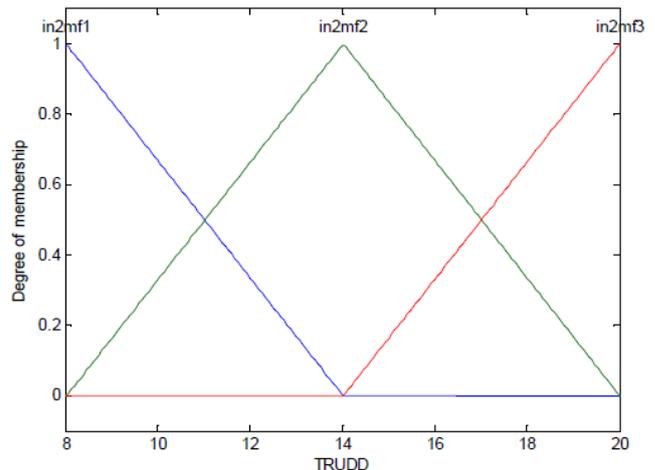


(D) Fourth Input Membership Functions Used to Fuzzify STR

Figure 4.4 Input Membership Functions for Developed SANFIS



(A) First Input Membership Functions Used to Fuzzify PTL



(B) Second Input Membership Functions Used to Fuzzify TRUDD

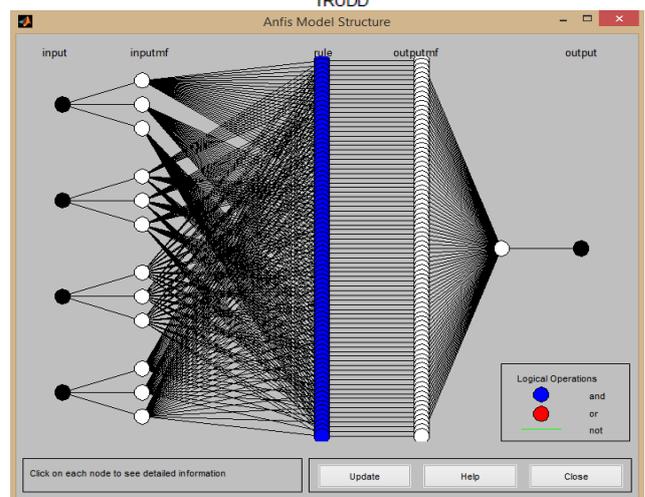
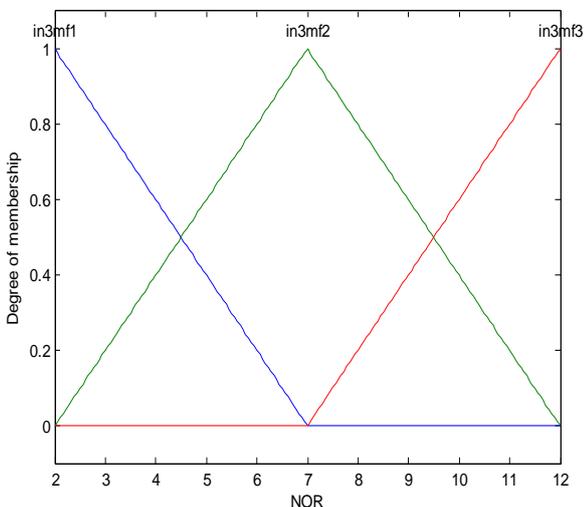


Figure 4.5 Developed SANFIS (MY\_ANFIS\_SRO.FIS) Basic Structure

**Table 2. Experimental Parameter Valued Used for Development and Training of FSANFIS**

Job	Processing Time at Lathe (PTL)	Time Remaining Until Due Date (Days) (TRUDD)	Number of Operations Remaining (NOR)	Shop Time Remaining (Days) (STR)	S/RO
A	15	12	4	10	0.5
B	10	15	5	7	1.6
C	20.4	12	7	5.5	0.928
D	18	17	8	15	0.25

**V. RESULTS AND DISCUSSIONS**

This section presents the results obtained after successful implementation of proposed work for incoming job sequencing based on priority calculation using Sugeno type adaptive Neuro fuzzy inference systems (SANFIS). Four jobs are considered here with four different processing times, due dates and number of operations and shop time remaining. They are determined based on customer requirements and no. of operations they perform on machines. Processing time here is the ideal time, means time needed if it was machined in just one machine. Table 3 shows the S/RO obtained for each jobs. Lower the value of S/RO parameter higher the priority.

**Table 3. S/RO Obtained Using SANFIS**

Job	Processing Time at Lathe (PTL)	Time Remaining Until Due Date (Days) (TRUDD)	Number of Operations Remaining (NOR)	Shop Time Remaining (Days) (STR)	S/RO
A	15	12	4	10	0.5
B	10	15	5	7	1.6
C	20.4	12	7	5.5	0.928
D	18	17	8	15	0.25

From table 3 it is clearly observable that, the lowest S/RO belongs to the job D and highest S/RO belongs to job B. Hence the obtained job sequence is D, A, C and then B.

**VI. CONCLUSIONS**

The work presented is directed towards investigating the applicability of fuzzy and adaptive Neuro techniques as a decision aid in the short-term control of flexible manufacturing systems. For this purpose a flexible manufacturing system for four incoming job cloud composed of four machines, one AGV, one load and one unload station and with routings and arrivals with fixed statistical characteristics was considered. A Sugeno type adaptive Neuro fuzzy scheduler is developed for job sequencing. This scheduler employs adaptive Neuro fuzzy logic system for calculation of incoming job priority based on S/RO parameter. This paper has brought forward a novel technique to increase performance by using Neuro fuzzy hybrid structure and also in giving a systematic design procedure (lacking in the literature) that takes into account multiple objectives and needs no interface with linguistic directions from human experts (e.g., management). In this paper, practical data are used to determine the job priority. Again, only job priority is taken into account, in future some other criteria's can also be added. Several parameters are used to design the problem, but, yet there may be other

parameters which can be added to make the model more accurate. All possible rules are taken, moreover if more parameters were added; number of the rules would have been increased. All this changes may lead the model to better results.

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